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Accounting for the effect of turbulence on wind turbine power curves

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Abstract. Wind turbines require methods to predict the power produced as inflow conditions change. We compare the standard method of binning with a turbulence renormalization method and a machine learning approach using a data set derived from simulations. The method of binning is unable to cope with changes in turbulence; the turbulence renormalization method cannot account for changes in shear other than by using the equivalent wind speed, which is derived from wind speed data at multiple heights in the rotor disk. The machine learning method is best able to predict the power as conditions change, and could be modified to include additional inflow variables such as veer or yaw error.

1. Introduction

Wind turbines operate in a wide variety of wind climates. For example, sites in the U.S. Midwest experience a large diurnal cycle of wind speed and turbulence, and offshore wind turbines in the North Sea in northern Europe experience severe gales and strong seasonal variation. Turbines at these sites, however, were likely developed and tested at other sites, also with different wind conditions. Recent research and industry experience has shown that the power output of wind turbines can vary dramatically at the same 10-minute average wind speed, as turbulence and other inflow characteristics change.

Although aeroelastic simulators are frequently used by turbine manufacturers to predict the performance of a wind turbine in a wide range of wind conditions, there is a need for simple models of wind turbine performance that can be used by site developers or consultants as part of the wind resource assessment and annual energy prediction process. Several methods have recently been developed to understand and predict the power of a wind turbine under a range of inflow conditions. This paper compares three different approaches to the problem:

- **Power curves using the “method of binning.”** Power data are binned according to wind speed, and the mean power and wind speed in each bin is used to create a power curve. This is the method set out in the 2005 International Electrotechnical Commission (IEC) standard on “Power performance measurements of electricity producing wind turbines” [1]. The power curve can then be used to predict the power at any wind speed, simply by finding the power at that wind speed.



- **Turbulence renormalization.** During power performance testing, wind speeds and turbulence are recorded and used to estimate a “zero-turbulence power curve.” When a new power curve is required, the effect of turbulence can be added back in to the power curve. This method is taken from Annex M of the 2013 committee draft of a new IEC power performance measurement standard [2].
- **Machine learning** can be used to create multivariable models of turbine performance, when sufficient information is available. This paper uses an ensemble of regression trees to predict the power as a function of several inputs, including shear, wind speed, and hub-height turbulence. This is known as the “random forest” method [3, 4].

This paper describes our experience with applying these performance predictions to data from aeroelastic simulations of a variable speed, pitch-regulated turbine. Our data are described in Section 2. In Section 3 we provide a detailed description of the methods used and the process that was followed. Results are presented in Section 4, and we make conclusions in Section 5. We anticipate that this paper will be useful for researchers and practitioners in the wind industry, as well as those working on standards.

2. Data sets

The data used in this study were derived from simulations of the response of the 1,500-kW WindPACT turbine to turbulent inflow. The turbine rotor diameter is 70 m, and it has variable blade pitch, and a variable-speed drive. Cut-in wind speed is 3 m s^{-1} , and rated wind speed is 11.5 m s^{-1} . Cut-out wind speed is 27.6 m s^{-1} . Details of the turbine are given by Poore [5] and Malcom [6]. The turbine was simulated in the aeroelastic code FAST [7], forced by 10-minute-long, turbulent wind fields from TurbSim [8]. The wind fields were configured to have a random distribution of turbulence intensity ($Ti = \sigma_u/U$, or the standard deviation of wind speed divided by the mean wind speed) in the range $Ti = [0,50]\%$, and shear exponent $\alpha = [-0.5,0.5]$. This study uses the results from approximately 1,500 10-minute simulations.

Simulations were post processed to extract the wind speed from the wind fields at multiple heights across the rotor disk. These data were used to determine the actual values of the mean wind speed at hub height, the turbulence intensity at hub height, the shear exponent, and the equivalent wind speed. The shear was quantified as the exponent of a power-law fit to the wind speed profile across the rotor disk. The equivalent wind speed is the wind speed that would have the same kinetic energy as the area-weighted sum of the kinetic energy at all heights in the rotor disk [9]. Figure 1 shows the range of forcing conditions. Power data were analyzed to find the 10-minute mean power in each 10-minute interval. The 10-minute data that are extracted from the simulations are similar to the variables that were used to create regression trees in [4].

The variation of power with shear and turbulence that was observed in the simulations is plotted in Figures 2a and 2b. The underlying power curve is clear, with power rising rapidly and then approaching a maximum at wind speeds greater than 12 m s^{-1} . The effect of shear is not systematic (Figure 2a), but the systematic impact of turbulence on power produced at a given wind speed (Figure 2b) is comparatively clear.

3. Methods

3.1. The method of binning

This is the industry-standard method for quantifying the power of a wind turbine versus wind speed, usually using data from a dedicated power performance test [1]. To create a power curve, data are filtered to remove nonstandard inflow or performance, and then binned into 0.5 m s^{-1} wide wind speed bins using the equivalent wind speed. The power curve is the relationship between the bin-mean power and bin-mean wind speed.

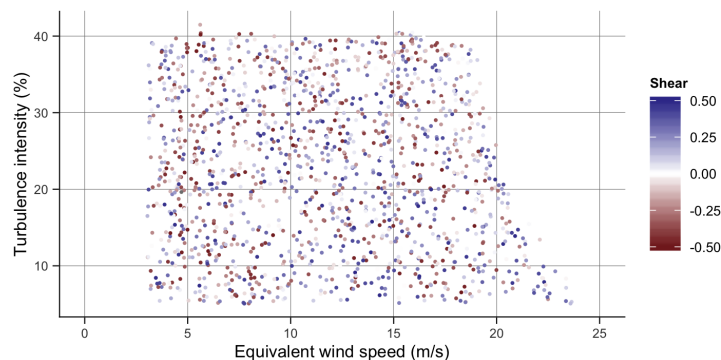
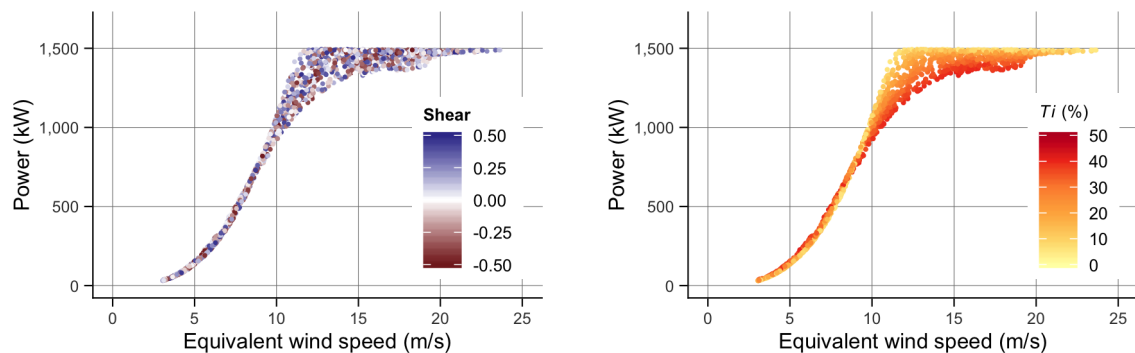


Figure 1: Distribution of shear exponent and turbulence in the data set. Each data point represents the mean shear and turbulence for a 10-minute wind field.



(a) Variation of 10-minute mean power with shear across the rotor disk

(b) Variation of 10-minute mean power with hub-height turbulence intensity

Figure 2: Performance of the WindPACT 1,500-kW wind turbine used in this study. Data are from simulations using the aerostructural simulator FAST, forced by TurbSim wind fields.

3.2. Turbulence renormalization

The wind speed and thus generator output power varies during a 10-minute interval as a result of turbulence. The turbulence renormalization method uses this concept to estimate the underlying power curve that would have the same overall performance if the variation in wind speed during a 10-minute interval followed a Gaussian distribution.

We are not aware of any publicly available implementations of the turbulence renormalization method in a data processing code such as R or MATLAB, and existing documentation is mostly descriptive, rather than showing the sequence of operations. The following section therefore includes flowcharts to allow others to replicate this research using their own data.

3.2.1. First estimate of the zero-turbulence power curve Ten-minute average data from a power performance test are used to create a power curve using the method of binning. The required data are described in this paper as the *training data*, and they include the following:

- Mean wind speed $u(k)$ over 10 minutes, corrected for density
- Standard deviation of the wind speed during the 10 minutes, $\sigma_u k$
- Turbulence intensity $Ti(k)$ at hub height, defined as $100 \times \sigma_u(k)/u(k)$

- 10-minute average generator power $P(k)$
- Rotor area A ,

where the index k indicates the 10-minute average value. Note that this paper uses the equivalent wind speed, which allows some accounting for the effect of wind shear [9].

The binned wind speed and power are used to calculate the power coefficient (C_p) and rated power, which are used to find parameters for the initial zero-turbulence power curve. For the initial zero-turbulence power curve, the turbine is considered to produce rated power at all wind speeds from rated wind speed to 100 m s^{-1} [2].

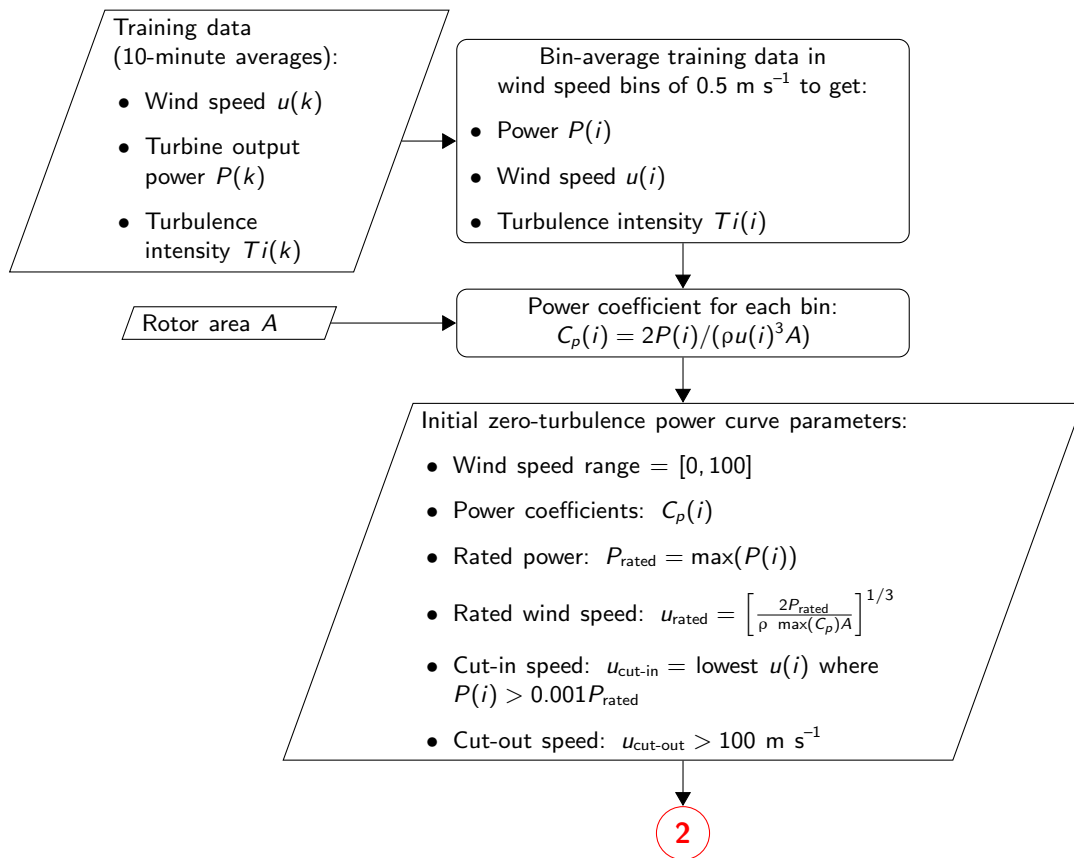


Figure 3: Process for obtaining the initial zero-turbulence power curve from training data

3.2.2. The theoretical zero-turbulence power curve This power curve is derived using the process shown in Figure 4. The theoretical zero-turbulence power curve is based on the initial zero-turbulence power curve, and is used to numerically simulate the power in each wind speed bin of the observed power curve. The numerically simulated power (\hat{P}) is the integral of the product of the theoretical zero-turbulence power curve and the frequency of different turbulence intensity levels in each bin. We observed that this numerically simulated power curve was slightly sensitive to the chosen integration method. An iterative process is used to get the closest agreement between the binned observations and the numerically simulated power curve. This process recognizes that the power in a 10-minute interval is a function of the distribution of the turbulence intensity during that period. Following [2], it is assumed that the turbulence intensity in each wind speed bin follows a Gaussian distribution.

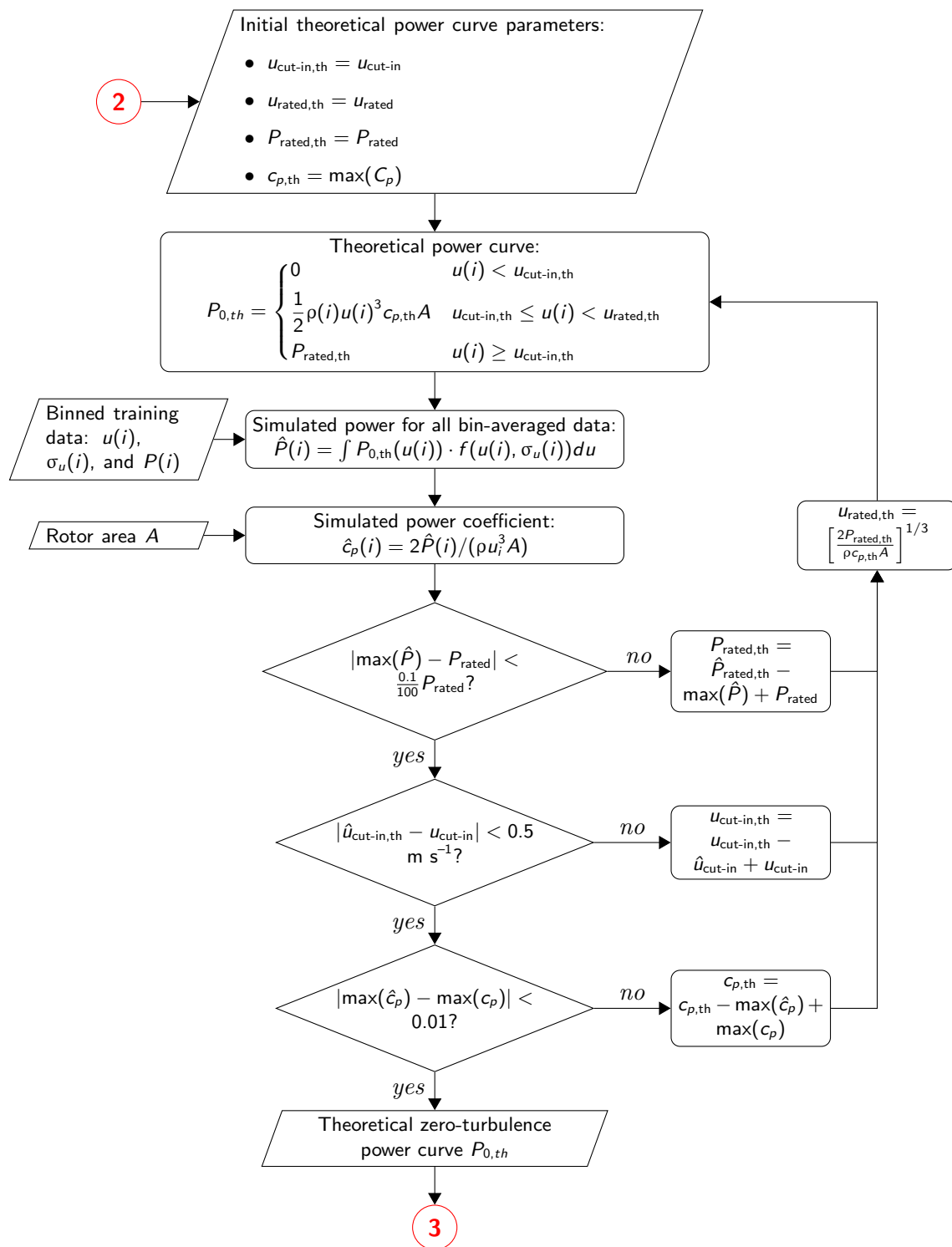


Figure 4: Process for obtaining the theoretical zero-turbulence power curve from training data

3.2.3. The zero-turbulence power curve Next, the theoretical zero-turbulence power curve is used to estimate the power output for the training data (Figure 5). Because there will still be a difference between the simulated and observed power generation, this value is added to the zero-turbulence power curve. Data are then bin-averaged to calculate the power curve.

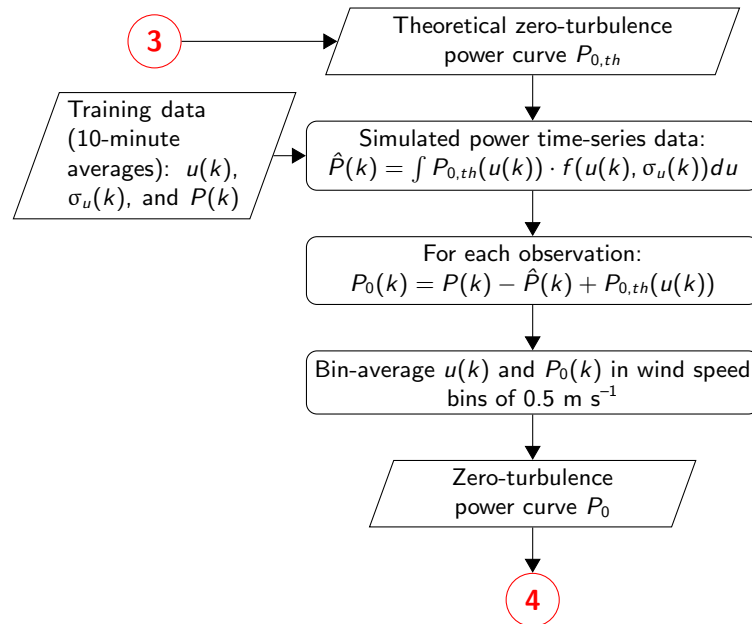
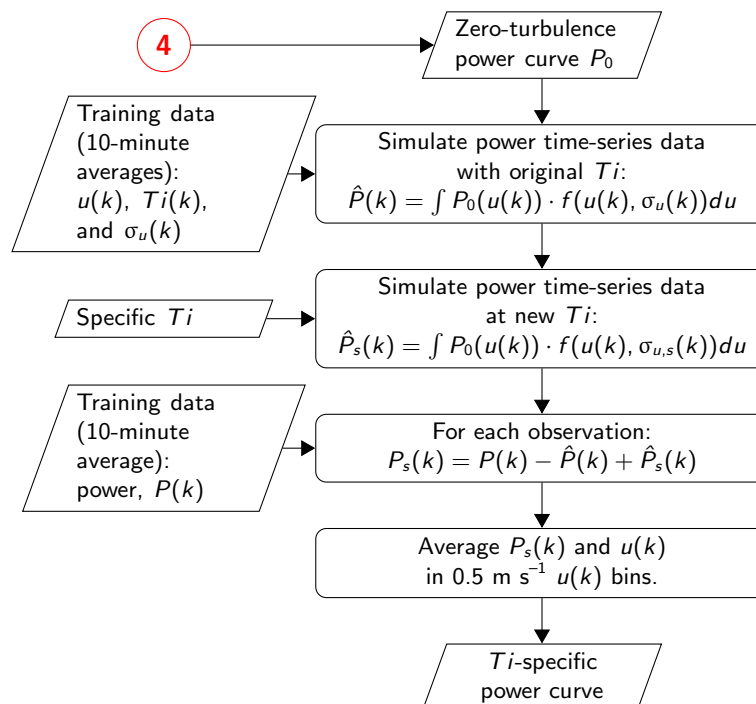


Figure 5: Process for obtaining the final zero-turbulence power curve from training data

3.2.4. Applying the zero-turbulence power curve to a new site The power produced by the turbine at a specific combination of wind speed and turbulence can be predicted by simulating the power curve at each new Ti value (Figure 6), and then querying that power curve to find the power produced at a specific wind speed.

Figure 6: Process for obtaining a power curve for a specific Ti value

3.3. The random forest method

This method uses an ensemble of regression trees to estimate the response of a system to forcing. A regression tree can be visualized as starting with a single set of forcing variables that are then passed along a branch, where each branch is a series of questions that terminates in a single leaf. The leaf represents a single, unique prediction of the response of the system to the forcing (Figure 7). Often an ensemble of many trees is used to reduce the overall uncertainty of the prediction, and so the approach is known as the “random forest” method. The power predicted by the random forest method in this paper is the mean from 100 trees. The method presented here was implemented in the R software environment [10] using the “randomForest” package [3]. Clifton *et al.* [4] describes a similar method using regression trees that was implemented in MATLAB.

In this study, the forcing conditions for the random forest method are the same as for the turbine renormalization method, with the addition of the turbine operating region (TOR), which relates to the turbine’s controller. The TOR is I when the mean wind speed is below cut in, II from cut-in to rated speed when the power output is roughly proportional to the cube of wind speed ($u_{cut-in} < u(k) < u_{rated}$), and III when the mean wind speed exceeds rated speed and the turbine blades are pitched toward feathered to limit power capture to the generator’s rated power ($u(k) > u_{rated}$). The response is the 10-minute average generator power, $P(k)$.

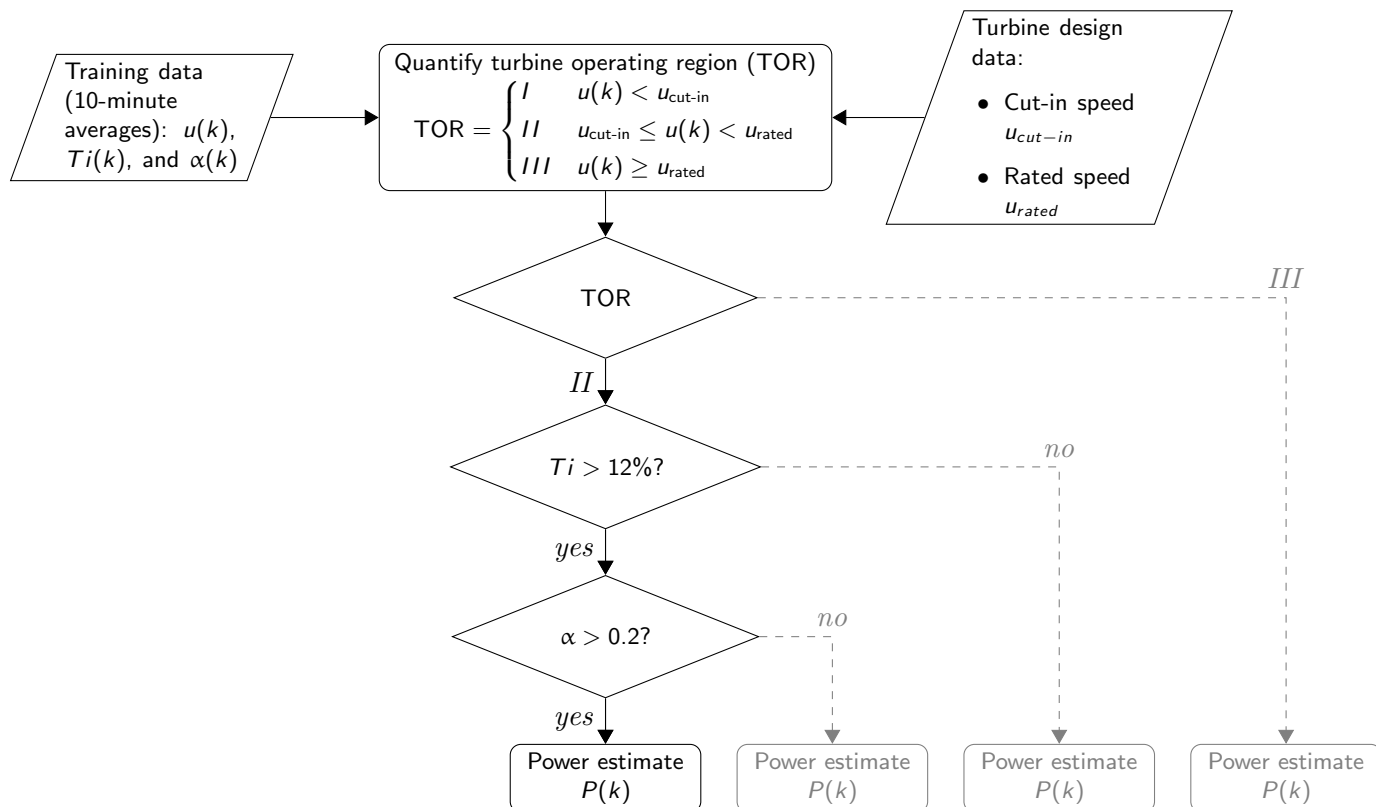


Figure 7: Schematic view of data inputs and the process implemented in one part of a regression tree. Depending on the decision that is made, a different path may be taken to an estimate of the power $P(k)$ associated with the input data.

4. Results

If the method of binning were used on the data set presented in Section 2 to create a power curve, it is clear that the power near the transition from Region II (power proportional to u^n) to Region III (constant power) of the power curve would be a strong function of the turbulence intensity. This could be important if a turbine were tested in a low-turbulence environment but then deployed in a high-turbulence location. Under such conditions, the performance at the new site would be noticeably reduced compared to expected. Conditional sampling of the power curve to a range of turbulence intensity would not solve this problem, because Figure 2b suggests that a site-specific power curve would also require the correct mean Ti and distribution of Ti at the site of interest.

We next consider how the turbulence renormalization method can be applied. Theoretically, the turbulence renormalization method should be capable of taking data acquired at one site, and adjusting those data so that they can be used to predict the power at another site with different turbulence characteristics. To test this assumption, we divide the data into two subsets according to the turbulence intensity. We create one subset with $Ti = [5,15]\%$, and another with $Ti = [15,30]\%$. Each subset is used to train the turbulence renormalization method, and the resultant model is tested against the other subset (Figure 8). To make results easier to compare, we apply the method of binning to the observed test data and the predictions of the test data. If the turbulence renormalization worked perfectly, the power curves for the test data would overlap. Figure 8, however, shows that our implementation of the turbulence renormalization method appears to overcompensate for the effects of turbulence, leading to an overestimate of the power when going from high to low turbulence, and an underestimate when going from low to high turbulence.

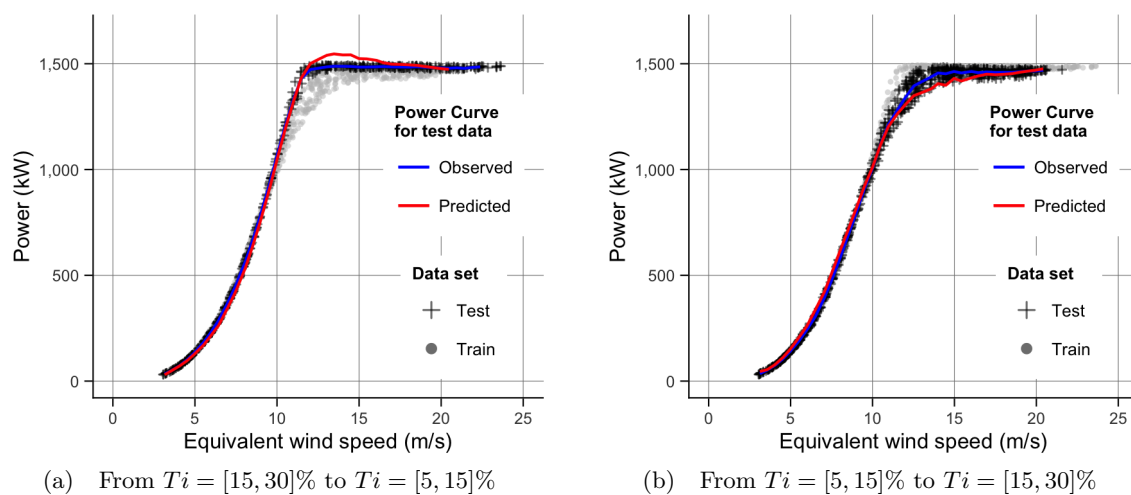


Figure 8: Results of using data with a certain Ti range to predict power in another Ti range. Plots show the data observed in both the training and test Ti ranges (points) and the power curves for the test range that were obtained by the method of binning.

The random forest method uses observations of the turbine forcing (inflow conditions) and the turbine response (power) to train — or educate — a regression tree model of the turbine performance. The model can then be used to predict the response of the turbine to previously unseen inflow conditions. The random forest method can only predict the response to conditions if it has already been trained with data that bracket those conditions. This limitation arises from

to the fact that the model is a statistical model of response to forecasting, instead of a physics-based model. For example, the approach used in Figure 8 to test the turbulence renormalization method would show the random forest method to work poorly, because the method would have no prior knowledge of the response in the high- or low-turbulence region. Instead, to illustrate how the machine learning method can be used, the model is trained using the entire data set, and then used to predict the power produced at constant shear ($\alpha = 0.2$) with different $Ti\%$ levels. The resulting power curves are plotted in Figure 9. Near rated speed, the random forest models clearly show the change in performance as a result of changes in turbulence. An unusual effect is observed, however, at wind speeds less than 5 m s^{-1} where the predicted power deviates from what we would expect from experience. This is an “edge effect” that is due to the training data set only including data that show the turbine producing power. As a result, the random forest model has no way to know that a turbine actually produces 0 kW at low or high wind speeds. If a random forest model is to be used in practice, the model training data should include a very wide range of forcing conditions to make sure that edge effects are reduced.

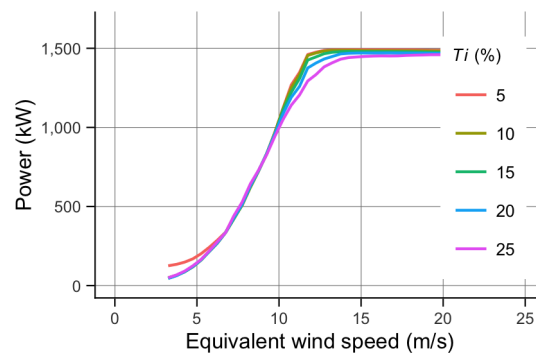


Figure 9: Power curves for specific Ti values created using the random forest method

Finally, we create models of the power performance using the method of binning, the turbulence renormalization method, and the machine learning approach. Then, we use each model to predict the power for each of the input data points. The power predicted using each model is compared with the observed power in Figure 10. The root mean square error (RMSE) between the observed and predicted values is shown for each method in the subplots.

The turbulence renormalization method visibly reduces the spread of data compared to the method of binning; while the random forest method clearly has the lowest spread and RMSE. From Figure 10, the error of the turbulence renormalization method increases near rated power. This error appears to be coupled to relatively high uncertainty near rated wind speed (Figure 8), suggesting that the turbulence renormalization method may need a model that includes some information about the turbine’s control system or the turbine’s aerodynamics.

5. Conclusions

A series of models of turbine power performance have been presented and tested using data from simulations. The simplest model is the method of binning, which is the current industry standard. The other methods are turbulence renormalization, which is a method set out in the current draft for a new IEC power measurement standard, and the random forest method. Both of these models require information about the turbulence, and can use shear data if available. The turbulence renormalization method and the random forest method capture the variation in turbine performance caused by turbulence better than the method of binning, which has no way to do this other than conditional sampling. The most accurate method for this data set is

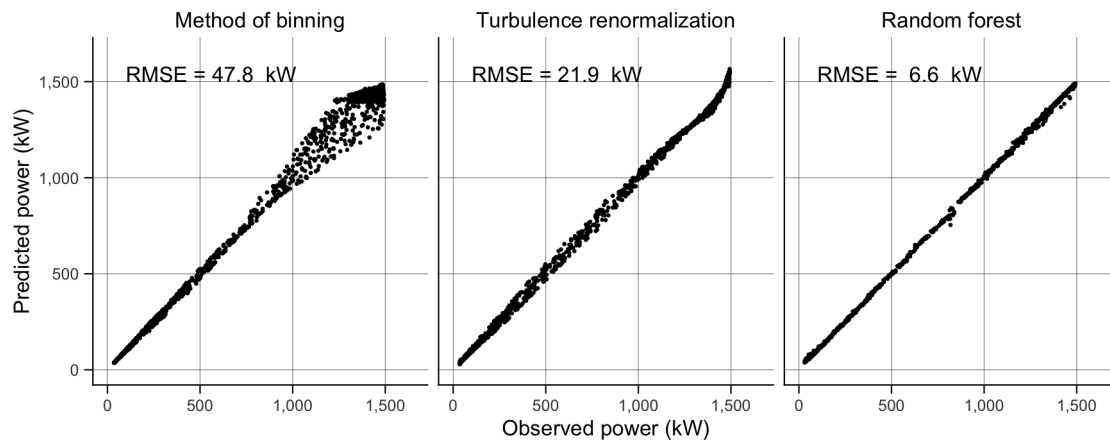


Figure 10: Comparison of the observed power and the power predicted using each of the three models discussed in this paper. The RMSE between the observed power and the value predicted by each method is shown.

the random forest method, which is also more flexible than the other methods because it can be expanded to take any input variables. We are in the process of testing the methods reported here with power performance test data from several utility-scale turbines, and expect to be able to present results from a wide variety of sites and atmospheric conditions in the near future.

Acknowledgments

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